From ERP to Advanced Resource Planning: Improving Operational Performance by Getting the Inputs Right

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Abstract

In this paper, we show that the planning and decision support capabilities of the MPC (Manufacturing Planning and Control) system, which forms the core of any ERP package, may be greatly enhanced by including an Advanced Resource Planning (ARP) module as an add-on at the midterm planning level. This ARP module enables to estimate the impact of variability, complexity and dynamic system behavior on key planning parameters. As such, it yields realistic information both for short-term planning purposes and for reliable lead time quotations. We show how dynamic behavior impacts the operational performance of a manufacturing system, and discuss the framework for incorporating the ARP module into the ERP system.

1. Introduction

The emergence and widespread adoption of ERP systems undoubtedly constitutes one of the most pervasive changes in the business environment over the past decades. According to [25], the term ERP can be interpreted in two ways. From the point of view of the IT community, the emphasis is on *integration*: an ERP system is a software tool enabling to integrate the different application programs (HR, finance, sales, marketing, production planning,…) in a company, by efficiently tracking all transactions in real time and sharing them across all functions through a common database. In the light of today's market environment, one can view the integration aspect of ERP as a prerequisite for further improvement. Organizations are increasingly aware that the next step in increasing profit and market share consists in engaging in effective supply chain management [13]. Indeed, the emergence of the specialized company has led to a surge in the number of partners contained in a single chain. Moreover, these partners tend to be spread around the globe. The success and widespread implementation of ERP systems has laid the groundwork for further integration across the entire supply chain.

On the other hand, managers of a company tend to emphasize the *planning* aspect: an ERP system should be able to support decisions regarding the planning and execution of the business. ERP systems in fact evolved out of traditional Manufacturing Planning and Control (MPC) systems. As shown in Fig. 1 (adapted from [25]), the MPC system still constitutes the core of any ERP system. It reflects the hierarchy of planning, with Sales and Operations Planning (SOP) on the long term level, Master Production Scheduling (MPS) and Material Requirements Planning (MRP) at the midterm level, and Shop Floor Control (SFC) and Supplier Systems at the short term level.

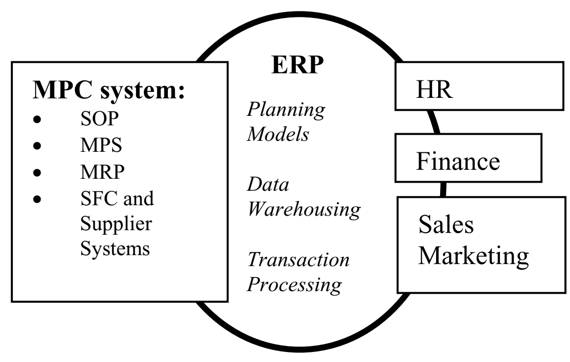

Figure 1. The scope of the ERP system

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The feasibility of the operational improvements that managers expect from an ERP implementation (such as lead time reductions, realistic capacity planning, improved on-time delivery) largely depends upon the effectiveness of the embedded MPC system. In this paper, we show that the capabilities of the MPC system may be greatly enhanced by explicitly recognizing the variability, the complexity, the limited production capacity and the dynamic behavior of manufacturing systems.

Variability is inherent to real-life systems, both at the demand side and at the supply side. Recent research in the Operations Management and Operations Research fields (e.g., see [16], [12], [4], [1]) has shown that variability has a substantive impact on the dynamic behavior of a manufacturing system, and hence on operational parameters such as production lead times and obtained customer service levels. Though ERP requires these parameters as input to the MPC planning module (e.g., for lead time offsetting in MRP calculations), current systems are not yet equipped to take this impact into account: the input parameters for the MPC module are mostly estimated (or simply fixed) in an ad hoc fashion. This often leads to unrealistic parameter settings, which undermine the effectiveness of the MPC system. In the following sections, we will point out that this dynamic behavior is an inescapable consequence of system variability, and that good estimates of this behavior are a prerequisite for a successful MPC system.

Traditional transaction oriented ERP systems not only ignore the importance of resource allocation decisions under uncertainty (variability), but also largely ignore the impact of limited production capacity. For instance, limited production capacity necessitates inventory in order to meet customer service objectives.

Finally, manufacturing systems nowadays operate in an increasingly complex environment. The surge in product customization and the emphasis on time-based competition complicate planning efforts, and require today's businesses to be increasingly responsive. In terms of the MPC system, this translates into the need for planning tools that not only yield realistic information on planning parameters, but are also able to generate this desired output in 'no time'.

To respond to these issues, we propose to extend the ERP system with a so-called ARP (Advanced Resource Planning) module, which enables to capture this dynamic system behavior on the midterm planning level. The primary objective is to obtain a more accurate and realistic view on the company's key operational indicators, such as effective capacity utilization, lead times, lot sizes and customer service (fill rate). Current ERP systems end up issuing plans and revisions to these plans on a frequent basis. Fire-fighting becomes the norm, resulting in suboptimal production scenarios, suboptimal capacity utilization and poor customer service. The benefits of our ERP add-on will be perceptible in all major functional areas of the company:

(1) Scheduling: As the midterm plans devised by the MPC system will be based on more realistic information, it will be easier for the schedulers to devise short-term plans which fit within the anticipated time windows. This entails both operational and financial advantages. As the effectiveness of the schedule improves, the people which are responsible for executing the schedule have little incentive to deviate from it, and hence schedule stability is improved. Moreover, material and components will be launched as needed, preventing shortages or excess of work-in-process on the shop floor. In this way, the company avoids unnecessary investments in working capital.

(2) Sales and marketing: For companies working in a make-to-order environment, it is vital that the lead time quoted to the customers is reliable. The functionality of the ARP module allows to dynamically adjust lead time quotations to changes in demand or shop floor conditions, such that the sales department's promises are in sync with the manufacturing department's capabilities and due date performance is secured.

(3) Strategic and operational decision making: As explained in the next sections, the ARP module allows managers to fine-tune both strategic decisions (such as capacity investments, outsourcing decisions) and operational decisions (such as lot sizing) in view of the operational targets they want to achieve (e.g., lead time reduction). As such, the ARP module not only provides a tool for analysis, but also a lever for operational improvement.

(4) Improved coordination in the supply chain: Supply chain coordination is key in today's business world. ARP may be instrumental in achieving better coordination. It brings advantages not only for the company's customers (who obviously draw benefit from realistic lead time quotations), but also for its suppliers. As the timing and quantity of purchase orders are generated by the MRP system based on the company's own build schedule, a stable schedule at the level of the company will translate into a more reliable order pattern (less expediting or de-expediting, fewer quantity changes, fewer rush orders,…) perceived by the supplier. In this way, the improved transparency and data accuracy provided by the ARP implementation improves supply chain effectiveness, and helps to mitigate one of the primary sources of the bullwhip effect.

(5) The human aspect of ERP: Planning systems that are inefficient and consequently create a constant re-planning attitude on the part of your people are highly demotivating. This aspect is often ignored when evaluating MPC systems. An ARP module will set the parameters right from the very beginning (i.e., on the aggregate level), which avoids constant re-planning and improves the human aspect of the organization.

These benefits have been confirmed by real-life implementations of the ARP module (see [21]). Given its widespread impact on the performance of the company, the move towards ARP is of strategic importance for top management: the adoption of ARP will result in a better use of the capacity structure, a better allocation of working capital, improved relationships with suppliers, and higher customer and employee satisfaction.

The ARP module that we propose is based on rough-cut modeling approximations ([16], [15]), which permit a quick evaluation of the parameters of interest. It will be shown that the integration of an ARP module into an ERP system can be carried out in a relatively straightforward way, as most of the input data for the module should be readily available from ERP databases. The development of the ARP engine should ideally be taken care of by the ERP system developers, to ensure compatibility and smooth data exchange.

In the next section, we present some fundamental insights on the behavior of dynamic systems, and their implications for MPC modeling and management decision making. In Section 3, we present a framework for the integration of ERP and ARP. Section 4 outlines the conclusions, and summarizes the limitations and benefits of our approach.

2. Basic system dynamics

In this section, we present some fundamental insights about the dynamic behavior of a stochastic system. Figure 2 shows the basic factors which determine the performance of a manufacturing system, such as lead time behavior and customer service levels (on-time delivery performance).

The major determinant of lead time behavior is the *effective utilization* of the manufacturing system (see [4]). Utilization is an average concept, which results from the confrontation of demand and supply. The demand side represents the customers, who place orders and consequently put a load on the manufacturing system. This load depends on both the quantity and timing of all incoming customer orders. On the other hand, the supply side represents the capacity, i.e., the resources (which may consist of machines, transportation resources, personnel etc.) of which the manufacturer disposes in order to fulfill customer demands. On the midterm planning level, these resources are typically limited in capacity: though capacity may be increased (or decreased) to a certain extent, the amount of capacity available is not infinitely flexible. Moreover, resources are not always available for production: planned and unplanned outages (such as shift patterns, preventive maintenance or equipment failures) decrease the capacity of the resources at hand.

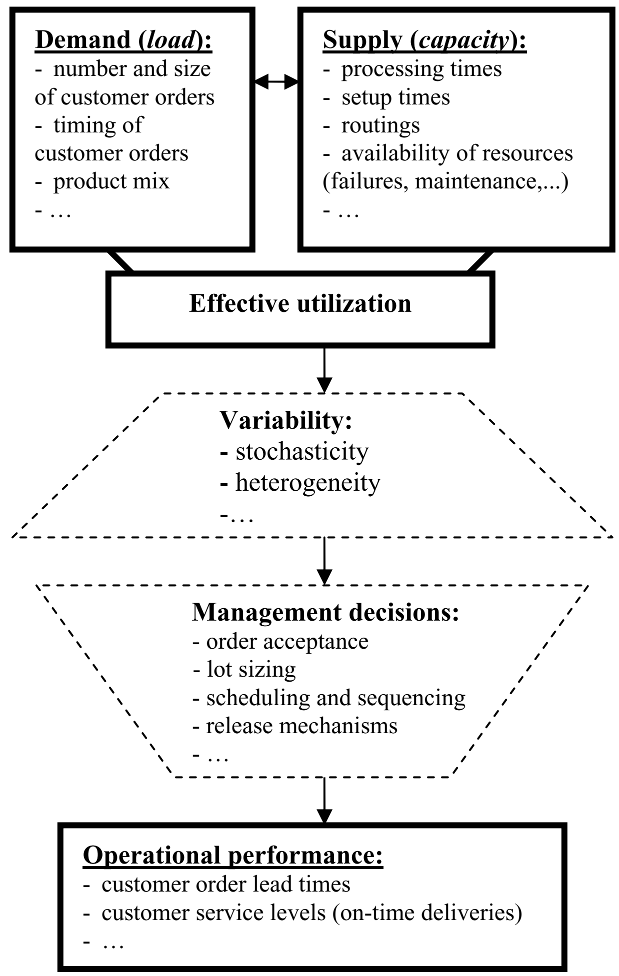

Figure 2. Determinants of operational performance of a manufacturing system

The resulting capacity, taking into account all "outages" (e.g., machine breakdowns, quality problems, material shortages, setup times) is called the *effective capacity*. As the effective capacity is finite,

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the load that is put on the system will result in competition for resources. In a system that is subject to variability, this competition causes congestion, and average lead times will increase.

Congestion occurs even when the ratio between load and effective capacity is such that the system remains feasible (effective utilization below 100%). The relationship between effective utilization and average lead time performance is highly nonlinear, as depicted in Fig. 3 (see [4]). Moreover, variability acts as an amplifier on congestion: the higher the variability in the system, the more congestion will occur for a given effective utilization.

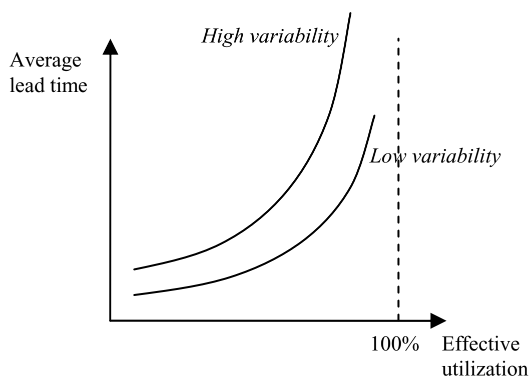

Figure 3. Relationship between effective utilization and average lead time

The effect demonstrated in Fig. 3 may be illustrated by queuing expressions, which enable to estimate the average lead time of a production entity through an individual resource. A production entity may be a single unit or a process batch of a given size; in general, any flow unit may be considered. Denoting the average lead time by *E(T)*, we may write the following generic expression:

$$E(T) = \frac{\left(c_a^2 + c_e^2\right)}{2}\frac{\rho}{\left(1-\rho\right)}t_e g + t_e \,.$$

The first term of this expression refers to the average waiting time in queue of a production entity at the resource, and hence measures congestion. For the M/G/1 system, the factor *g* equals 1, and the formula is exact (see e.g. [9]). For G/G/1 systems, the expression is approximative; different values for *g* have been proposed (see e.g. [1], [10] and [26] for further information). In the other components of the expression, we may recognize the different factors discussed in Fig. 2:

- the notation c_a^2 represents the squared coefficient of variation of the aggregate interarrival times of production entities at the resource, and hence captures the variability in the demand timing;
- the notation c_e^2 refers to the squared coefficient of variation of the aggregate effective processing times of production entities on the resource, and captures the impact of variability on the supply side as well as variability in product mix and quantity at the demand side (see e.g. [1], [10] and [26] for further information);
- the notation t_e refers to the average effective processing time for a production entity on the resource (see [4]), and ρ represents the effective utilization of the resource.

The term $\rho/(1-\rho)$ illustrates that the average lead time increases in a highly non-linear fashion for increasing values of the effective utilization. On top, the term $(c_a^2+c_e^2)$ demonstrates the corrupting influence of variability: higher variability leads to more congestion. Both effects were illustrated in Fig. 3.

Any real-life manufacturing system is subject to variability, and will hence inescapably behave as depicted in Fig. 3. Indeed, at the demand side, the timing and quantity of customer orders are typically stochastic. At the supply side, processing and setup times are usually stochastic too, and dependent upon the product type in case of a heterogeneous product mix. Unavailability of the resources adds further variability to the supply side.

From Fig. 3, we may draw a number of conclusions that are a prerequisite for good manufacturing planning practice. Firstly, it is fundamental to recognize the importance of both limited effective capacity and variability when developing plans at the midterm level, as these are the drivers of lead time behavior. Current MPC systems however contain no tools to evaluate effective capacity or variability, let alone to adequately model the resulting dynamics. Secondly, it turns out that high utilization and low average lead times are incompatible in real life systems. Planning your system at full capacity (effective utilization of 100%) is infeasible: this would cause the average lead time to soar to infinity ([4]). Even an effective utilization close to 100% causes the manufacturing system to be out of breath, leading to unacceptably long lead times due to the long waiting times, and moreover to vast amounts of money tied up in working capital.

In traditional ERP systems, lead-time is considered as fixed regardless of the level of effective utilization; consequently, lead times are often dramatically underestimated. The fundamental trade-off which is shown in Fig. 3 should be taken into account when devising material and capacity plans: in current MPC systems, no link is made between the two performance measures, leading to plans which often assume both high capacity utilization (often in view of “efficient” resource utilization) and attractive (target or “wishful thinking”) lead times, and hence are inherently unrealistic. The consequences of this approach will be primarily noticeable on the short-term (SFC) planning level: unrealistic targets at the midterm level unnecessarily complicate the scheduling effort, and lead to nervousness and increased fire-fighting behavior on the shop floor. Moreover, these efforts will likely be to no avail: smart scheduling is rarely able to correct for fundamental errors made at the midterm planning level. Only realistic lead time information allows a manager to determine acceptable release and due dates, i.e. providing the right time windows for scheduling and sequencing on the operation level ([17]).

While variability acts as an amplifier on congestion, management decisions (see Fig. 2) may impact system performance in both a favorable or unfavorable way. Decisions regarding order acceptance, lot sizing (including both process lot sizing and transfer lot sizing), scheduling and sequencing, and order release may influence the effective utilization of the system as well as the inherent system variability (see e.g. [3], [6], [7], [8], [11] and [23]). The relationship between lot sizing and lead time has been the most thoroughly studied up to date. It is now widely accepted that the relationship between process lot size and average lead time is convex (e.g., [5] through [8], [11], [12], [22], [23], [24]), implying that there exists an optimal lot size minimizing average lead time. This insight has led to the development of optimization procedures, which make use of the convexity property to determine the "optimal" process lot sizes for a given objective function in multi-product multi-machine settings (see e.g. [12], [22] and [24] for applications of these procedures).

In contemporary planning systems, lot sizing decisions are mostly taken in an ad hoc fashion, determined by means of a cost optimization procedure (such as EOQ or Wagner Whitin based procedures), or determined by a scheduler (mostly based on a heuristic). Regardless of the approach used, the impact on effective utilization and lead time behavior is currently ignored. This may lead to dangerous situations, particularly in environments with long setup times. In these settings, applying lot sizes that are too small may cause the effective utilization to rise beyond 100%, *de facto* leading to an infeasible system. For that reason, the incorporation of an optimization procedure into the planning system at an aggregate (midterm) level would undoubtedly constitute a major advance in the management decision support capabilities of the MPC system.

While the discussion so far has focused on average lead time behavior, it is primordial to recognize that, as the manufacturing system is subject to variability, the resulting lead time (of customer orders, process lots, etc.) will be a stochastic variable too. The factors shown in Fig. 2 (effective utilization, variability, and management decisions) will also impact the variability of the lead time, and even the entire lead time probability distribution. Research ([3], [17], [20]) has revealed that the lead time distribution is typically positively skewed (as shown in Fig. 4), with a heavy tail. Insight into the lead time distribution is primordial in three respects. Firstly, it impacts issues regarding customer service levels. Indeed, the percentiles of the lead time distribution determine the customer service level that the company will obtain for a given agreed lead time. Equivalently, insight into the distribution supports managers in quoting realistic lead times to their customers, in view of obtaining a target customer service level.

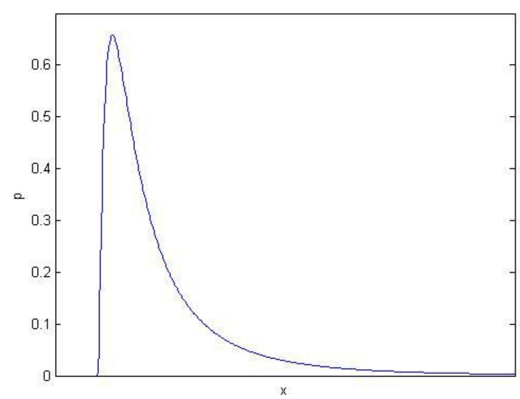

Figure 4. Illustration of lead time probability distribution

Secondly, it promotes realistic lead time offsetting in the Material Requirements Planning (MRP) context. In order to ensure due date compliance and robust schedules in production, the lead times used in MRP should incorporate safety time. This safety time can be quantified from the lead time percentiles, and determines a realistic time window for order release and order completion. Hence, an adequate estimate of the lead time distribution is essential for a stable and smoothly running MPC system. The safety time issue also has implications on the practical design of ERP systems. E.g., it has been shown that it is advisable to limit the number of levels in the Bill-Of-Material, for the simple reason that detailed allocated safety time is inferior to pooled safety time ([20]). In other words, the design of the ERP system itself will impact lead time performance.

Thirdly, the information on average lead times and lead time percentiles is also crucial for developing robust card-based Production Activity Control (PAC) systems, such as KANBAN, POLCA (see [14]) or CONWIP (see [4]). Indeed, the average lead time will impact the average number of cards that need to be present in the system (this follows from Little's law, e.g., see [4]), while information on the lead time percentiles is useful when determining the number of safety cards necessary to protect the target throughput rate against variability (see [2] for an illustration). In the absence of adequate lead time information, card levels are set rather ad hoc or based upon experience; this may either lead to missed throughput rates (when card levels are set too low) or to an unnecessarily high level of work-in-process on the shop floor (in case card levels are set too high).

3. ERP and ARP: framework

From the previous discussion, it is evident that the operational performance of an ERP system can be strongly enhanced by integrating an add-on ARP module, which enables to adequately quantify the stochastic, complex and dynamic behavior of the manufacturing system at hand. The ARP module should be situated at the midterm (material and capacity planning) level, as shown in Fig. 5.

The backbone of the ARP system is in fact an open queuing network model, which models the system on an aggregate level. Though this approach is approximative and does not enable great detail, we are confident that it is sufficiently precise for supporting midterm planning. Real-life applications of this open queuing network model speak in favor of this approximative model ([12], [18], [19], [21], [22] and [2]). Moreover, queuing network models require short run times, as opposed to (for example) discrete-event simulation models. As mentioned in Section 1, this aspect is crucial in order to support management decision making in today's complex environment. Another important advantage over discrete-event simulation is the fact that queuing network models are largely generic, making them particularly appropriate for what-if analyses and widespread use in different industry settings.

As the literature on open queuing networks is vast, we have chosen not to go into details regarding the technical expressions in this paper; the interested reader can find further information in e.g. [1], [12], [15] and [16]. Instead, we will focus on the interface of ERP and ARP, i.e., which input parameters are needed for the ARP module, and which output parameters are fed back into the MPC system.

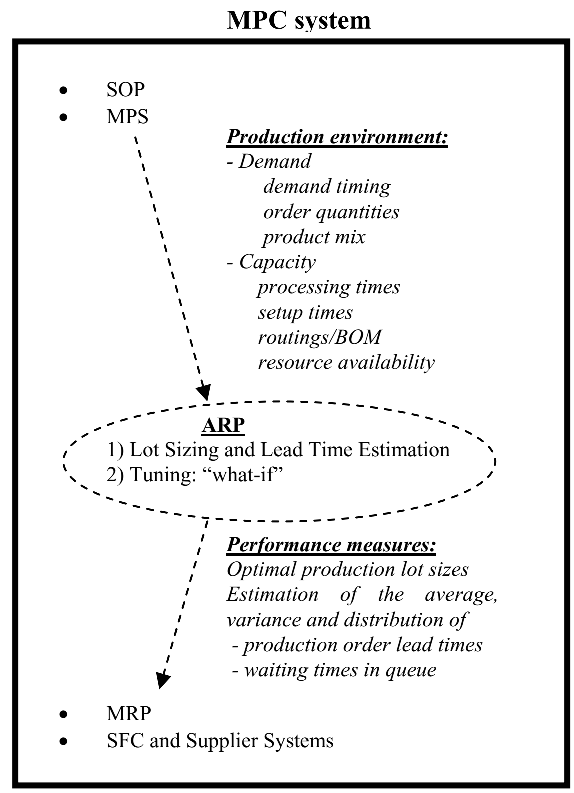

Figure 5. Framework for integrating the ARP module into ERP

As shown in Fig. 5, ARP uses input parameters which are available on the level of the MPS. As stated in [25], the MPS constitutes the anticipated build schedule for the company: it specifies the quantities of end products to be completed during the next planning period, with a required completion time. The MPS is usually constructed on a sufficiently long planning horizon (usually several months), and is mostly updated every couple of weeks. From the MPS, we obtain information about the demand side for the upcoming planning period (i.e., which products need to be produced, what is the timing of the demand, and what are the quantities). This information enables us to quantify the load, as well as the variability inherently present in the demand. On the other hand, the information about the supply side (such as routings of the products that must be produced, setup and processing times on the different workcenters, failure behavior of resources, planned outages) is usually available from standard company records (bill of material, routing files, resource files, resource availability lists) which are contained in the ERP database. This information is crucial for the ARP module, as it determines effective capacity.

The ARP module translates the characteristics of the production environment for the upcoming planning period into the following output estimates: optimal production lot sizes, average and variance of the order lead time, average and variance of the waiting times in queue in front of the different workcenters, and lead time distribution. This information may be retrieved for every end item and/or component. Two phases may be distinguished in the ARP procedure (see also [2] and [12]). During the lot sizing and lead time estimation phase, the manufacturing system is modelled as an aggregate queuing network in which all parameters are functions of the manufacturing lot sizes. By applying an optimization routine to this network, an optimal manufacturing lot size is obtained for every product type, along with estimates of the corresponding performance measures (average, variance and distribution of production order lead times and waiting times in queue). Next, the tuning phase enables management to adjust the capacity or demand structure through what-if analyses (by using overtime, implementing a capacity expansion, off-loading heavily loaded resources, or considering alternative routings) if the performance measures are considered unacceptable or if the proposed order portfolio leads to infeasibilities (e.g., resources which are used beyond effective capacity). Once the tuning phase is finished and management is satisfied with the estimated performance measures, the output is communicated to the next level in the MPC hierarchy, i.e. MRP, and further down to the level of SFC.

We may conclude that the integration of an ARP module into the current ERP systems may be done in a relatively straightforward way, as most of the required input data may be retrieved from ERP records. Hence, the ARP add-on can be merely considered as an intermediate calculation and optimization engine, necessary to enable robust planning and scheduling at the lower levels of the MPC system. The challenge, in our opinion, lies in ensuring that the information flow is managed in such a way that the ARP system delivers its full benefits, as discussed in Section 1. We think here for example of the timely dissemination of lead time related information to the sales department, in view of quoting delivery lead times. We'd also like to stress the need for updating the relevant information at the start of every planning period.

The main goal of any ERP system consists in enhancing transparency, knowledge and information management for the company and its customers (clients and suppliers). In this respect, the importance of the add-on ARP module in providing realistic (i.e. reliable) information can hardly be understated.

4. Conclusion

In this paper, we have proposed the development of an Advanced Resource Planning module, as an add-on to current ERP systems. This ARP module enables the planner to capture the relationship between variability and uncertainty on the one hand and capacity utilization, inventory (lead time) and customer service on the other hand. The approach is based on queuing approximations, and offers numerous benefits.

The ARP module provides support for management decision making at the midterm planning level. It allows for optimization of manufacturing lot sizes, and fine-tuning of the capacity and/or demand structure in view of obtaining target operational performance. As the approach is based on analytical models (instead of, for instance., simulation), the run time for these what-if analyses is typically very short, offering managers the timely decision support needed in today's complex and ever-changing environment.

The output of the ARP module consists of realistic estimates of key planning parameters, such as expected production lead times and estimates of required safety times. These estimates offer useful information for different departments of the company. Firstly, they offer critical information to the schedulers, by determining realistic time windows for scheduling and sequencing, and setting reliable production order release dates. The ARP module stimulates the pro-active attitude of planners: as a result, nervousness and fire-fighting behavior on the shop floor are avoided. When a card-based PAC system is used, the information is crucial for determining a robust level of work-in-process necessary to obtain a given throughput rate. The estimates also offer the necessary information for reliable lead time quotations by the sales department.

One limitation of the approach is that it only offers estimates of the required parameters. As the ARP engine consists of a queuing model, the resulting output is approximative. This drawback is, however, hard to avoid. In order to capture the complexity of real-life manufacturing systems, queuing modelers have no choice but to resort to approximations. While simulation may offer larger precision than the queuing approach, we believe it is ill-suited for the intended purposes, as the resulting models are not generic and require long run times.

Another limitation lies in the fact that current queuing models are not yet able to adequately reflect all specificities of today's manufacturing environments. Many opportunities remain in extending and further fine-tuning the current models. This presents a continuing challenge for the research community.

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